Comparison of PSDA and CCA detection methods in a SSVEP-based BCI-system

Gido Hakvoort, Boris Reuderink, and Michel Obbink

University of Twente, Faculty EEMCS,
P.O. Box 217, 7500 AE, Enschede
The Netherlands

Abstract. Using steady-state visually evoked potential (SSVEP) in brain-computer interface (BCI) systems is the subject of a lot of research. One of the most popular and widely used detection method is using a power spectral density analysis (PSDA). Lately there have been some new methods emerging, one of them is using canonical correlation analysis (CCA) which seems to have some promising improvements and advantages compared to traditional SSVEP detection methods, like better signal-to-noise ratio (SNR), lower inter-subject variability and the possibility to use harmonic frequencies, i.e., a serie of frequencies which have the same fundamental frequency. In this research two different SSVEP detection methods, one using PSDA and one using CCA are compared. The results show that the CCA-based detection method performs significantly better than the PSDA-based detection method. The increase of performance can in particular be seen when using harmonic frequencies. While the PSDA-based detection method has difficulties detecting harmonic frequencies, the CCA-based detection method is able to detect harmonic frequencies.

1 Introduction

A brain-computer interface (BCI) can be described as a communication link between brain and machine. In a BCI system, signals from the brain are being analyzed to determine the user's state of mind or intentions. BCI systems have been used to help disabled users by giving back mobility and breaking the isolation of people with physiological disorders such as amyotrophic lateral sclerosis (ALS). For the signal acquisition there are many different measurement methods e.g., electroencephalography (EEG), magnetoencephalography (MEG), functional magnetic resonance imaging (fMRI) or near-infrared spectroscopy (NIRS). All of them are non-invasive methods requiring no surgical procedures and each of them with its own strengths and weaknesses. Especially in the area of healthy user BCIs research, EEG measurements have become very popular as its temporal resolution is very good and relatively cheap.

One of the most used signals in EEG-based BCI systems are event-related potentials (ERPs) which are brain responses that are the direct result of an external or internal event. These ERPs usually occur when the brain is exposed to any kind of visual, somatosensory or aural stimulus, mental activity, or when omitting a stimulus that was repeatedly occurring. One member of the ERP family is steady-state visually evoked potential (SSVEP) [1,5]. In most cases SSVEPs are triggered by presenting a stimulus with a periodic pattern, normally at frequencies above 5 Hz, to a user. The periodic pattern of the stimulus can then be traced back in the measured brain signals and are mostly recorded from the occipital region of the scalp [1,8]. As the power of a SSVEP matches that of the stimulus its power only covers a narrow bandwidth [7] making it relatively easy to detect.

For detecting the presence of SSVEPs there have been many different methods, one of the most popular and widely used is power spectral density analysis (PSDA). From a time window of the user's EEG-signal the power spectral density (PSD) is estimated using a fast fourier transform (FFT). The magnitude of each stimulation frequency can then be used for further classification. Using canonical correlation analysis (CCA) is a relatively new approach to detect the presence of SSVEPs. The use of CCA seems to have some promising improvements and advantages compared to the traditional PSDA-based detection methods, like better signal-to-noise ratio (SNR), lower inter-subject variability and the possibility to use harmonic frequencies [2,6].

When using a LCD monitor to present different stimuli, research is limited to only a few number of frequencies due to the refresh rate of the monitor. This number is even further reduced by traditional SSVEP detection techniques, like PSDA-based detection, that have troubles identifying stimuli flickering at harmonic frequencies. In an online BCI environment it is desired to have a good working SSVEP detection method which is not limited in its selection of frequencies. Since traditional SSVEP detection techniques have difficulties identify stimuli flickering at harmonic frequencies and will in most cases classify these as their first harmonics, using a CCA detection method might provide some improvements.

Research has shown overall improvements while using a CCA-based detection method, especially in the SNR and inter-subject variability [2,6]. However there is little known about the differences in classification accuracy between the two different SSVEP detection methods in respect to frequencies and harmonic frequencies.

In this research the two different SSVEP detection methods are compared to find an answer to the question if and how a CCA-based detection method improves the classification accuracy of different frequencies compared to a PSDA-based detection method. It is expected that a CCA-based detection method does indeed improve the classification accuracy of different frequencies, especially harmonic frequencies. First there will be some background information on stimuli frequencies, PSDA-based detection and CCA-based detection. In the methods section both detection methods and the experimental setup will be explained in more detail. After this the results of the experiment will be reported which is followed by the discussion and conclusion.

2 Background

2.1 Stimuli frequencies

Using a LCD monitor to present stimuli for a SSVEP-based BCI system has great advantages. BCI systems become more portable as they can operate on basic notebooks and because the user interface is at the same place as the stimuli source there is no need for users to make great changes in their gaze. However the use of a LCD monitor does also have some disadvantages. Because SSVEPs are triggered by a stimulus with a periodic pattern, the stimuli source has to alternate between two different colors. This alternation can only be done at the refresh rate of a LCD monitor and because two separate frames are needed, the highest reachable frequency is a factor 2 of the refresh rate. Since most LCD monitors have a refresh rate of 60 Hz, the highest reachable frequency is often 30 Hz.

Volosyak *et al.* [9] have studied the use of different frequencies based one the refresh rate of a LCD monitor. They compared two sets of frequencies, the first set contained a set of regular frequencies (13.00 Hz, 14.00 Hz, 15.00 Hz, 16.00 Hz and 17.00 Hz) and the second set contained frequencies that are integer factors of the refresh rate (6.67 Hz, 7.50 Hz, 8.57 Hz, 10.00 Hz and 12.00 Hz). Their result showed that the second set of frequencies is more suitable for presenting stimuli on a LCD monitor. The factor of the refresh rate produce a more stable stimuli frequency because only whole frames are visible on the LCD screen. The idea of using factors of the refresh rate as stimuli frequencies will be used in this research.

2.2 PSDA-based detection

There have been many different SSVEP detection methods which are based on PSDA. They rely on the fact that a periodic pattern with the same frequency as the stimulus frequency or one of its harmonics can be traced back in the brain signals. When a SSVEP is present in the brain signals, the magnitude of its periodic pattern only covers a narrow bandwidth and can easily be measured in the frequency domain.

One PSDA-based detection methods, described by Cheng *et al.* [3] will be used in this research. In their research, subjects had to insert a telephone number. On a computer screen there were thirteen buttons, ten with numeric values, a backspace, an enter and one for on/off. Each button flickered at a different stimuli frequencies between 6 Hz and 14 Hz, excluding harmonic frequencies and alpha rhythms which were determined for each subject individually to minimize the interference of spontaneous EEG.

The EEG data had a sample rate of 200 Hz and was filtered with a bandpass filter of 4 Hz - 35 Hz. Every 0.3 seconds a 1024 points FFT was performed using the latest 512 data samples padded with zeros. The average magnitude was multiplied by two and used as threshold. If the sum of the magnitudes of a stimuli frequency and its second harmonic exceeded the threshold, it was considered that the subject was gazing at this frequency. If the same frequency was detected in multiple FFTs, 4 for the on/off button and 6 for the other buttons, it was selected and the action was executed.

Eight of their thirteen subjects gave promising results, some subjects performed very good with a bit rate of almost 1 bps. But others performed badly with a lowest bit rate of around 0.01 bps.

2.3 CCA-based detection

Canonical correlation analysis is a type of correlation technique that focuses on two sets of variables [4]. Its strength is that it tries to find pairs of linear transformations for the two sets such that when the transformations are applied the new sets of variables have a maximal correlation. Some new upcoming SSVEP detection methods are using CCA. Detection methods based on CCA also rely on the fact that a periodic pattern with the same frequency as the stimulus frequency or one of its harmonics of can be traced back in the brain signals. However, instead of measuring the magnitude of a periodic pattern as with PSDA-based detection methods, CCA-based detection methods measure the correlations between the brain signals and the given stimuli frequencies.

One described by Lin *et al.* [6] which has been used and redefined by Bin *et al.* [2] will be used in this research. In the research of Bin subjects had to insert a phrase of 30 characters using 6 buttons on a LCD monitor, each flickering at a different stimuli frequency. The CCA-based detection methods described by both Lin and Bin use EEG data from multiple channels as the first set of variables. Lin used CCA for the selection of channels and although the selection differed slightly between subjects, SSVEPs could be traced back in recordings from the occipital region of the scalp. Bin recorded EEG data, without any channel selection, from nine different channels *O1, O2, Oz, PO7, PO8, POz, P3, P4* and *Pz* with a window length of 2 seconds. For each of the stimuli frequencies a compound of reference signals was created and used as the second set. The stimuli frequency with the highest correlation between the first and second set was eventually selected.

Twelve subjects participated in Bin's experiment and the CCA-based detection showed promising results, one of the most important conclusions for this research is that harmonic frequencies can be used coincide and are still detectable using a CCA-based detection method.

3 Methods

3.1 Experimental Setup

For the BCI experiment a LCD monitor [1] was used to present the stimuli. In the center of the screen there was a small white cross placed on a black background, see Figure 1 for the screen layout. All subjects were seated in a comfortable chair

[1] Samsung SyncMaster 203B, 20", 60Hz, 1280x1024

at approximately 70 cm in front of the monitor and were requested to focus on the white cross. During the experiment subjects were exposed to 7 different types of trials, in which the presented stimulus varied in size and frequency. In each trial one stimulus, a blinking white circle, appeared at the location of the cross. The subject had to focus for 4 seconds on the stimulus. Between trials, subjects had 6 seconds rest to relax their vision. All trials were presented 25 times and were placed in a random order prior to the experiment, thus for each subject, 25 segments of 4 seconds of data were recorded for each different trial. The complete experiment lasted 60 minutes and was divided in 4 sessions of equal length. Between the sessions, subjects could relax in order to reduce the effect of visual fatigue.

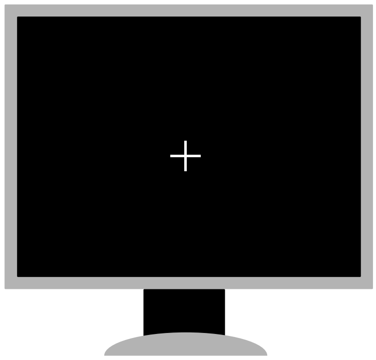

Fig. 1. The screen layout on the monitor

3.2 Data acquisition and processing

In the meantime, continuous EEG activity was recorded for offline analysis using a BioSemi ActiveTwo system[2] with a sampling rate of 512 Hz. Recordings were taken from 32 scalp electrodes, placed according to the international 10-20 system.

3.3 Stimuli parameters

When using a LCD monitor to present different stimuli, research is limited to only a few number of frequencies due to the refresh rate of the monitor. This number is even further reduced by traditional SSVEP detection techniques that have troubles identifying stimuli flickering at harmonic frequencies. Flickering frequencies of 6 Hz, 6.67 Hz, 7.5 Hz, 8.57 Hz, 10 Hz, 12 Hz and 15 Hz, which

[2] BioSemi, Amsterdam, The Netherlands

correspond to ten, nine, eight, seven, six, five and four frames in one flickering period are used in this research. All frequencies were tested with a light sensor to ensure their correctness.

During the experiment the stimuli also varied in sizes of 2 or 3 centimeter, in the offline analysis the smallest size was left out of this research.

PSDA-based detection In the offline analysis for PSDA-based detection, trials were classified using an algorithm based on work of Cheng *et al.* [3]. The EEG data from *Oz* was filtered with a bandpass filter of 4 - 35 Hz. common average reference (CAR) is applied to the signal and a FFT was performed every 0.3 seconds with a FFT-size of 512 data points. For each of the k stimuli frequencies the sum of the extracted magnitudes of its first and second harmonics (f_1, f_2) were used for classification. The stimuli frequency with the highest value, which also exceeded two times the average magnitude of the FFT, was classified as the presented frequency (1). For frequencies which did not fit within the frequencies resolution of the FFT, which was 1 Hz, linear interpolation was used on the two surrounding frequencies. The first two classifications of the 4 second stimuli were dropped as they contain non-stimulated data and might influence the performance. The rest of the classifications are used in a majority vote to determine the presented frequency.

$$2 * \overline{FFT} < \underset{i}{\operatorname{argmax}}\, f_{1_i} + f_{2_i} \qquad i = 1, 2, \ldots, k, \tag{1}$$

CCA-based detection Canonical correlation analysis is a type of correlation technique, like Pearson product-moment correlation coefficient (PMCC) or multiple regression analysis (MRA). All these correlation techniques use variables with observed values. Now let $\mathbf{x}$ and $\mathbf{y}$ denote two discrete random variables and let X and Y denote two sets with m and n variables respectively. Where PMCC focuses on the relationship between two variables $(\mathbf{x}, \mathbf{y})$ and MRA focuses on the relationship between one variable and a set of variables $(\mathbf{x}, Y)$, CCA focuses on two sets of variables (X, Y)[4]. If two sets of multidimensional variables have a strong linear relationship, this might not even be detected by other correlation techniques due to the used coordinate system. The strength of CCA is that it tries to find pairs of linear transformations (W_x, W_y) for the two sets of variables such that when the transformations are applied, the coordinate systems are maximally correlated (2). The projections of these linear transformations are called the canonical variates.

$$(W_x, W_y) = \underset{W_x, W_y}{\operatorname{argmax}} |corr(XW_x, YW_y)| \tag{2}$$

In the offline analysis for CCA-based frequency detection, trials were classified using an algorithm based on work of Bin *et al.* [2]. Figure 2 gives an illustration of how CCA was used for frequency detection in a SSVEP-based BCI system with k classes, with stimulus frequencies $f_1, f_2, \ldots, f_k$. For each trial, S

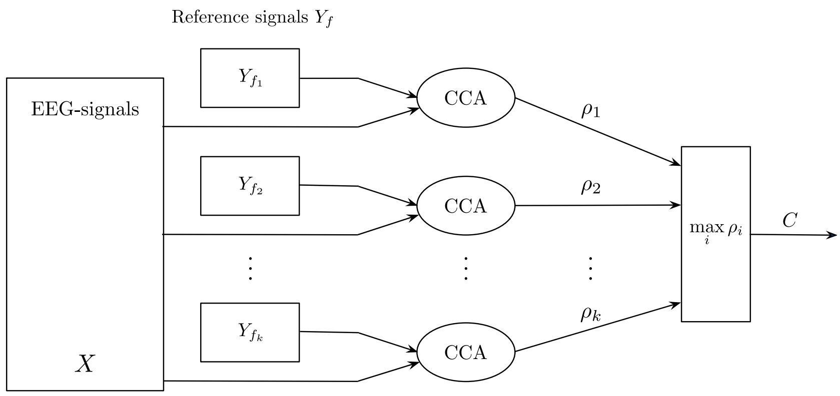

Fig. 2. An illustration of how CCA can be used for frequency detection with k classes [2]. X is a set of EEG-signals and Y_f is a set of reference signals. C is classified as $\max_i \rho_i$, where ρ_i is the highest correlation of the CCA and $i = 1, 2, \ldots, k$

seconds of EEG data from eight different electrodes (*Pz, P3, P4, PO3, PO4, Oz, O1, O2*) were defined as X. Y_f denotes a set of reference signals which were defined as in 3, where f_s is the sampling rate, T is the sampling period ($\frac{1}{f_s}$) and H is the number of harmonics, which was set to 3. For the reference signals both *sine* and *cosine* were used to ensure an optimal minimum correlation of $\frac{1}{\sqrt{2}} \approx 0.7071$.

$$Y_f = \begin{pmatrix} sin(2\pi f t) \\ cos(2\pi f t) \\ \vdots \\ sin(2\pi H f t) \\ cos(2\pi H f t) \end{pmatrix}, \qquad t = \frac{1}{T}, \frac{2}{T}, \ldots, \frac{S\ f_s}{T} \tag{3}$$

For the classification, both X and each of the reference signals in Y_f were used as input for the CCA method. The transformations W_x, W_y returned by the CCA methods were applied to the original data in X and Y_{f_k} resulting in the canonical variates $U = XW_x$ and $V = Y_{f_k} W_y$. Both U and V have the same number of variables, equal to $\min(m, n)$. Of the new correlations between U and V, the sample canonical correlations, only the highest correlation was used for the frequency detection. The detected class C was classified as in 4.

$$C = \max_i \rho_i, \qquad i = 1, 2, \ldots, k, \tag{4}$$

where ρ_i are the results of the CCA for each of the reference signals $f_1, f_2, \ldots, f_k$.

3.4 Subjects

Seven right-handed subjects (one female and six males), between 21 and 26 (μ=24.3, σ=1.6) years of age participated in the experiment. All subjects had normal or corrected-to-normal vision and described themselves as daily-based computer-users. Five users had no experience with EEG or BCI-systems, the others at least once. Before the experiment all subjects signed an informed consent.

4 Results

Tables 1 and 2 show a confusion matrix of the average recall (in precentage) of the PSDA-based and CCA-based detection methods respectively, with rows representing the presented frequency and columns representing the classified frequency. The recall is defined as $\frac{tp}{tp+fn}$ where tp is the number of true positives and fn is the number of false negatives.

Table 1. The confusion matrix for the PSDA-based detection method showing the average recall. With the rows being the presented frequencies and the columns the classified frequencies.

	6	**6.67**	**7.5**	**8.57**	**10**	**12**	**15**
6	74.86	3.43	2.29	6.29	13.14	0.00	0.00
6.67	48.57	27.43	7.43	4.00	12.57	0.00	0.00
7.5	44.00	4.00	37.14	5.14	9.71	0.00	0.00
8.57	34.29	11.43	5.14	42.29	6.86	0.00	0.00
10	28.00	5.14	5.14	2.86	58.86	0.00	0.00
12	58.86	3.43	3.43	4.57	8.57	21.14	0.00
15	33.14	4.00	32.57	1.71	14.29	0.00	14.29

Table 2. The confusion matrix of the CCA-based detection method showing the average recall. With the rows being the presented frequencies and the columns the classified frequencies.

	6	**6.67**	**7.5**	**8.57**	**10**	**12**	**15**
6	62.29	3.43	8.00	4.57	21.14	0.57	0.00
6.67	13.71	46.29	17.14	10.29	12.00	0.57	0.00
7.5	11.43	4.00	65.71	5.71	11.43	1.14	0.57
8.57	8.00	6.86	5.14	68.57	10.86	0.57	0.00
10	4.00	5.71	3.43	5.14	80.00	1.71	0.00
12	23.43	2.86	4.57	6.29	10.29	52.57	0.00
15	10.29	5.71	16.00	8.00	20.00	0.57	39.43

Both PSDA-based and CCA-based detection methods seem able to detect the presented frequency with an average recall above change level. But there are some clear differences. Looking at the average recall for the PSDA-based detection method (Table 1), one of the first things that stands out are the low recall values of 12 Hz and 15 Hz, which in most cased have been misclassified as their fundamental frequencies, namely 6 Hz and 7.5 Hz. It can also be seen that the PSDA-based detection method is biased towards 6 Hz. Looking at the average recall for the CCA-based detection method (Table 2), it seems to cope a lot better with the harmonic frequencies. The same tendency for the classification of 12 Hz and 15 Hz is still visible, but less than with the PSDA-based detection method. There is also an increase visible for the recall of other frequencies.

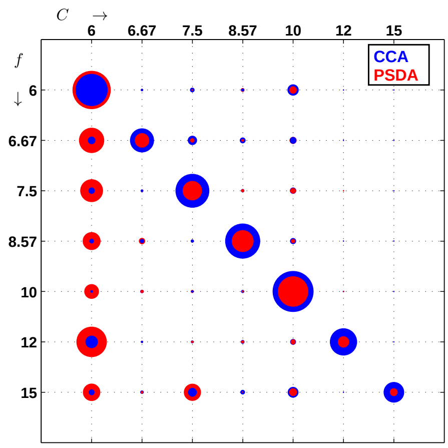

Fig. 3. An illustration of the average recall for the PSDA-based and CCA-based detection methods. Larger circles represent a higher recall, f is the presented frequency and C the classified frequency.

All these observations can clearly be seen in figure 3 where red and blue circles represent the true positive rate (recall) of PSDA-based and CCA-based detection methods respectively, where f represent the presented frequency and C the classified frequency. Larger circles represent a higher recall.

Tables 3 and 4 show the precision of individual subjects, defined as $\frac{tp}{tp+fp}$ where tp is the number of true positives and fp is the number of false positives. From these tables it can be seen that the CCA-based detection method also has a higher recall than the PSDA-based detection method and that although the PSDA-based detection method has a higher recall for 6 Hz, its precision for 6 Hz is lower.

Table 3. The precision for each of the frequencies per subject for the PSDA-based detection method.

	6	**6.67**	**7.5**	**8.57**	**10**	**12**	**15**
Subject 1	16.11	7.69	20.00	0.00	100.00	0.00	0.00
Subject 2	18.03	0.00	54.55	50.00	50.00	100.00	0.00
Subject 3	54.35	100.00	54.76	96.15	100.00	100.00	100.00
Subject 4	32.61	87.50	69.23	100.00	30.86	100.00	0.00
Subject 5	16.33	20.00	15.79	17.07	50.00	0.00	0.00
Subject 6	42.11	100.00	94.12	100.00	43.86	100.00	100.00
Subject 7	18.58	14.71	0.00	28.57	40.00	0.00	100.00
Average	28.30	47.13	44.06	55.97	59.25	57.14	42.86

Table 4. The precision for each of the frequencies per subject for the CCA-based detection method.

	6	**6.67**	**7.5**	**8.57**	**10**	**12**	**15**
Subject 1	36.67	11.11	28.57	65.22	76.00	100.00	100.00
Subject 2	42.22	60.00	59.26	66.67	29.41	81.25	100.00
Subject 3	86.36	100.00	89.29	92.59	69.44	100.00	100.00
Subject 4	47.62	100.00	88.89	95.45	32.47	100.00	100.00
Subject 5	28.57	20.00	25.93	21.43	47.37	100.00	100.00
Subject 6	64.00	94.74	83.33	100.00	54.55	84.62	95.83
Subject 7	41.30	45.71	73.91	100.00	85.71	87.50	100.00
Average	49.54	61.65	64.17	77.34	56.42	93.34	99.40

Because there is little data and a normal distribution can not be assumed easily, a Wilcoxon test is used to determine if there is any significant difference between the two detection methods. Also outliers have less influence on a Wilcoxon test than on a t-test. All precision values of the frequencies from tables 3 and 4 were used as input for the Wilcoxon test, resulting in two variables with 49 observations. The Wilcoxon signed-rank test showed that the CCA-based detection method performed significantly better ($Z = -3.6306, \rho < 0.001$) than the PSDA-based detection method. Especially when looking at the harmonic frequencies of 6 Hz and 7.5 Hz, namely 12 Hz and 15 Hz, there can be seen a large increase in both recall and precision. The only frequency in which the PSDA-based detection method has a higher recall than the CCA-based detection method is with a stimuli frequency of 6 Hz, but then again, the PSDA-based detection method is biased towards 6 Hz.

5 Discussion

Overall the CCA-based detection method does improve both the precision and recall of different frequencies compared to a PSDA-based detection method.

That a lot of stimuli frequencies were often misclassified as 6 Hz when using the PSDA-based detection method could be an indication of an incorrect threshold. The low precision of 6 Hz also supports this idea. It is possible that despite of the fact that the value of a stimuli frequency exceeds the threshold, it was classified as a lower frequency simple because of the fact that its magnitudes were higher. When determining the threshold, the decreasing magnitude for higher frequencies was not taken into account which is valuable prior knowledge that should be used. This would also explain the low recall of the higher frequencies, 12 Hz and 15 Hz, which are known to be easier to detect.

The CCA-based detection method used multiple EEG signals which does increase the overall performance. However, using multiple EEG signals does not explain the large differences in precision and recall of 12 Hz and 15 Hz. The incorrect threshold with the PSDA-based detection method would have the same effect on multiple signals. Therefor, the large differences in precision and recall of 12 Hz and 15 Hz is an effect of using CCA itself.

In the experiment held for this research there was only one stimulus present during each trial on which a subject had to focus. In a real life BCI-system there would probably be multiple stimuli. This could have an influence on the detection rates, but this holds for both detection methods.

Both SSVEP detection methods used in this research do not require any form of training. Optimizing the algorithms for each subject (by training) will probably improve the classification rates for both detection methods. This could be done in future research along with incorporated the decreasing magnitude for PSDA or a combination of both detection methods which could improve both precision and recall.

6 Conclusion

In this research two different SSVEP detection methods were compared, one using PSDA and one using CCA. During a small experiment seven stimuli frequencies were presented to seven subjects. Both SSVEP detection methods classified the incoming EEG date in an offline setup. The results show that the CCA-based detection method performs significantly better than the PSDA-based detection method. The increase of performance can in particular be seen when using harmonic frequencies. While the PSDA-based detection method has difficulties detecting harmonic frequencies, the CCA-based detection method is able to detect different harmonic frequencies. Therefore, especially when the use of harmonic frequencies is desired, the CCA-based detection method is preferred over the PSDA-based detection method.

For future research it would be interesting to compare variations and combinations of both SSVEP detection methods used in this research. Where, for example, a variation could be a PSDA-based detection method which incorporated the decreasing magnitude of higher frequencies or a combination where CCA finds a new set of variables with a maximal correlation, which are then used in a PSDA.

References

1. F. Beverina, G. Palmas, S. Silvoni, F. Piccione, and S. Giove, *User adaptive BCIs: SSVEP and P300 based interfaces*, PsychNology Journal, 1 (2003), pp. 331–354.
2. G. Bin, X. Gao, Z. Yan, B. Hong, and S. Gao, *An online multi-channel SSVEP-based brain–computer interface using a canonical correlation analysis method*, Journal of Neural Engineering, 6 (2009), p. 046002.
3. M. Cheng, X. Gao, S. Gao, and D. Xu, *Design and implementation of a brain-computer interface with high transfer rates*, Biomedical Engineering, IEEE Transactions on, 49 (2002), pp. 1181–1186.
4. D. Clark, *Understanding Canonical Correlation Analysis*, no. 3 in Concepts and techniques in modern geography, Geo Abstracts Ltd, 1975.
5. M. Gerven, J. Farquhar, R. Schaefer, R. Vlek, J. Geuze, A. Nijholt, N. Ramsey, P. Haselager, L. Vuurpijl, S. Gielen, et al., *The brain–computer interface cycle*, Journal of Neural Engineering, 6 (2009), p. 041001.
6. Z. Lin, C. Zhang, W. Wu, and X. Gao, *Frequency recognition based on canonical correlation analysis for SSVEP-based BCIs*, Biomedical Engineering, IEEE Transactions on, 53 (2006), pp. 2610–2614.
7. M. Lopez, F. Pelayo, E. Madrid, and A. Prieto, *Statistical characterization of steady-state visual evoked potentials and their use in brain–computer interfaces*, Neural Processing Letters, 29 (2009), pp. 179–187.
8. L. Ruen Shan, F. Ibrahim, and M. Moghavvemi, *Assessment of steady-state visual evoked potential for brain computer communication*, in 3rd Kuala Lumpur International Conference on Biomedical Engineering 2006, Springer, 2007, pp. 352–354.
9. I. Volosyak, H. Cecotti, and A. Gräser, *Impact of Frequency Selection on LCD Screens for SSVEP Based Brain-Computer Interfaces*, Bio-Inspired Systems: Computational and Ambient Intelligence, (2009), pp. 706–713.